Smart tablet-based gameplay identification of preschool children with autism: A replication study with machine learning data analytics improvements.

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Background

Human movements are prospective (Delafield-Butt et al., 2018). They must anticipate ahead of time their lawful consequences (Delafield-Butt & Gangopadhyay, 2013; Trevarthen & Delafield-Butt, 2017a, 2017b) and in development these become structured with serial ordering to generate narrative that form the basis of shared, embodied meaning-making (Negayama et al, 2015; Delafield-Butt & Adie, 2016; Trevarthen & Delafield-Butt, 2015; Delafield-Butt & Trevarthen, 2015). In children with autism, evidence indicates a common disruption to prospective movement may underpin its early pathogenesis (Trevarthen & Delafield-Butt, 2013; Torres et al., 2013) and may be a cardinal feature of autism (Fournier et al., 2006; Anzulewicz, Sobota & Delafield-Butt, 2016; Cook, Blakemore & Press, 2013) dependent on brainstem sensorimotor growth errors (Delafield-Butt & Trevarthen, 2017; Bosco et al., 2019).

In this study, we employed smart tablet computers with touch-sensitive screens and embedded inertial movement sensors to ecologically record the subsecond motor kinematics of purposive, prospective movements made by children developing with and without autism. In earlier analysis, we demonstrated machine learning computation of children's movement patterns identified ASD with 83% sensitivity and 85% specificity (Anzulewicz, Sobota & Delafield-Butt, 2016).

This poster presents data analytics improvements and conclusions on the identifying features of autism.

Aims

1. To achieve an accessible, serious game smart tablet identification of ASD in young children.
2. To determine the psychological aspects that identify autism in children's gameplay.

Objectives

1. Test the original performance accuracy with a new, generalised and larger data set.
2. Improve the machine learning analysis with simpler, generalised models.
3. Determine the features (variables) that differentiate children with autism from TD children.

Method

Participants. 118 children 3-6 years old clinically diagnosed with Childhood Autism (ICD-10 2010) and 420 age- and gender-matched typically developing (TD) children were added to the original study of 37 and 45 children, respectively. An additional 26 age-matched children with an other neurodevelopmental disorder (OND) that was not autism were included. Inclusion criteria: normal or corrected-to-normal vision, no other sensory or motor deficits. Exclusion criteria: Sensory, motor, or cognitive disability that prevented gameplay.

This produced two sets of participants, **(1) a Training and Validation Set** of 81 children with ASD and 375 TD children, and **(2) a Test Set** of 37 Children with ASD and 45 TD children (from Anzulewicz, Sobota, Delafield-Butt, 2016).

Serious Games. Two games (www.duckiedeck.com) running on iPad mini tablets (Apple Inc.) set within a bespoke app to organise the display of the games sequentially for a 2 minute training phase followed by a single 5 minute test phase with code for collecting inertial sensor and touch screen data (Play.Care, Harimata) was employed. Previous machine learning analysis demonstrated 93% classification accuracy based on 262 features (Anzulewics, Sobota, & Delafield-Butt, 2016).

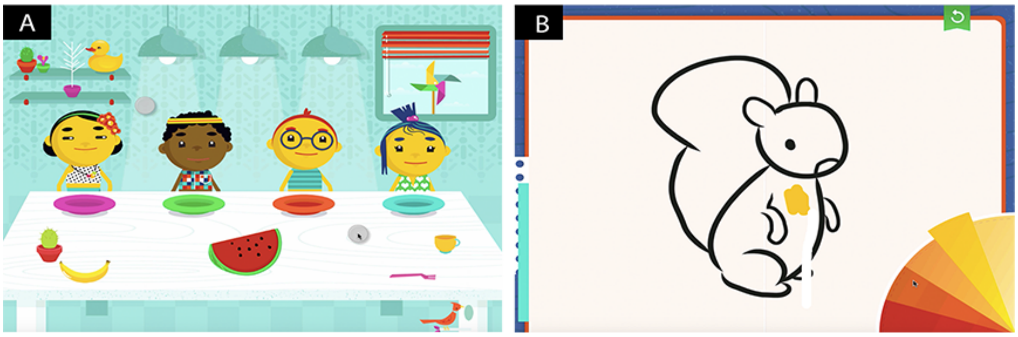


Figure 1. **Two serious iPad games.** **(A) Sharing** consisted of dividing a piece of food and distributing it evenly among four cartoon children present on the screen. When the food was distributed, all children exclaimed, "Yipee!" and proceeded to munch the food in a delightful manner for 3 seconds. Then, the trial repeated. **(B) Creativity** was a colouring game with no rules of engagement. An object outline appeared for tracing, then a colouring wheel appeared and the child could select a colour for colouring. The toy or animal outline always remained unobstructed.

Data Acquisition. **(A) Touch Screen** coordinate data (x,y) recorded at 60Hz and **(B) Inertial Movement Unit sensor** (tri-axial accelerometer, tri-axial gyroscope) data collected at 20Hz were obtained during gameplay.

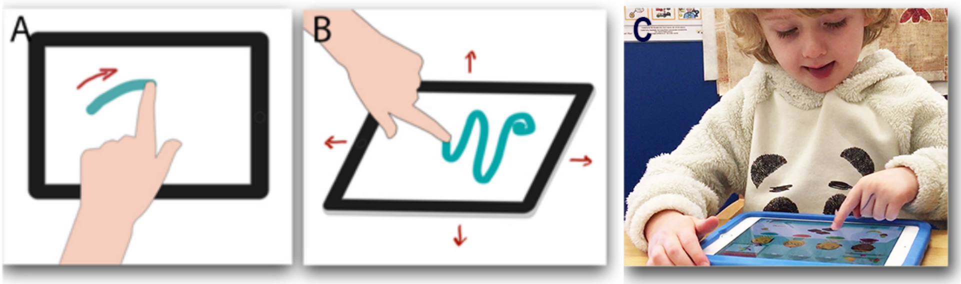


Figure 2. Data were collected on gesture (A) kinematics from the touch screen and (B) impact and pressure from the inertial sensors during (C) children's gameplay at the table.

Feature Sets for Machine Learning.

Three sets of features were computed from the touch and inertial sensor data. **Set A.** The original feature set of 262 features published in Anzulewics, Sobota & Delafield-Butt (2016). These variables were small computations of the raw touch and inertial sensor signals and described the overall motor and gameplay pattern using a single value for each game session, e.g. mean touch velocity, max touch velocity, standard deviation of touch velocity, *etc*. **Set B**. Images of gesture patterns derived from touch screen data only made by compiling five bins one minute each over a single game. **Set C.** Kinematic features based only on the touch screen data. Each gesture was time normalised and simple features computed to describe the motor pattern. Data points were binned and features computed for each, *e.g.* mean, median, quartiles and deciles. These data were analysed by (a) session mean and (b) individual movements.

Set A. Feature Reduction for Ensemble Methods

The original feature set of 262 features published in Anzulewics, Sobota & Delafield-Butt (2016) was reduced. These features are small computations of the touch and inertial sensor signals that described the overall motor pattern using a single value for each game session, *e.g.* mean touch velocity, max touch velocity, standard deviation of touch velocity, *etc*.

The original Set A features list was reduced by recursive feature selection and removal of low variance and high within-group correlations (Figure 3) and adjusted using t-SNE (Figure 4).

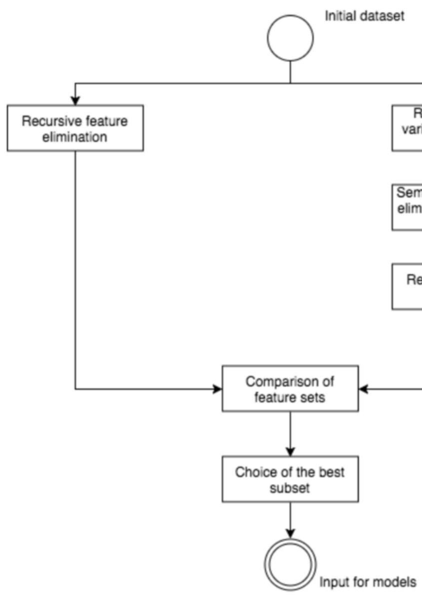


Figure 3. Flow diagram for reduction of features.

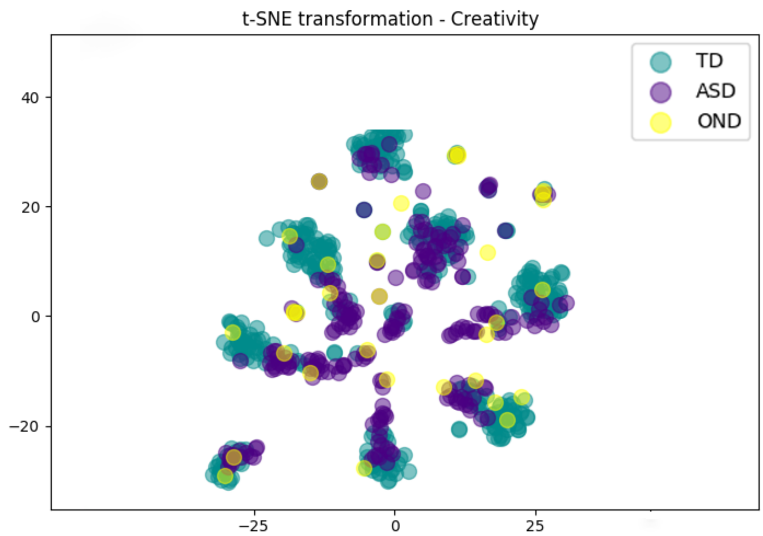


Figure 4. t-SNE transformation of data from the Creativity game

The features list reduced from 262 to <17 for each game (Table 1).

Table 1. Reduced features list and their description.

Sharing Food

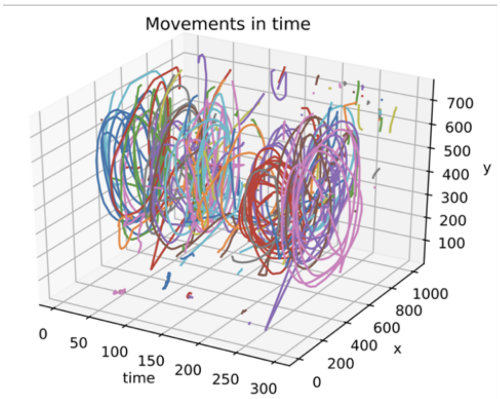
Feature name	Feature type	Data type
AvgGesturesArea	Mean area occupied by gestures, computed by a minimal adaptive polygon.	Touch
AvgGesturesJerk	Mean jerk of gestures.	Touch
TouchEventsPerGesture	Mean data points of gestures.	Touch
DirectnessIndexMax	Maximum distance of gestures.	Touch
AvgGestureDuration	Mean duration of gestures.	Touch
GesturesAccelerationMean	Mean acceleration of gestures.	Touch
GesturesWidthMean	Mean value of width (x-axis in landscape).	Touch
GesturesHeightMean	Mean value of height (y-axis in landscape).	Touch
HeatMapEmptyBlocksCount	Number of screen sectors with no gesture, computed from 10 x10 bins.	Touch
HeatMapFrequentClustersRate	Ratio of the number of data points in the most frequently visited bin to the all data points.	Touch
JerkMax	Maximum jerk of gestures.	Touch
AvgMovementSpeed	Mean velocity of gestures.	Touch
TouchGestureCount	Number of gestures.	Touch
Acceleration mean magnitude	Mean accelerometer value irrespective of axis.	Inertia
AttitudeRange_z	Range (max-min) of gyroscope z-axis.	Inertia
AttitudeZeroCrossingRate_z	Frequency of sign change of gyroscope x-axis.	Inertia

Creativity

Feature name	Feature type	Data type
DirectnessIndexMax	Maximum distance of travel of a gesture	Touch
AvgGestureDuration	Mean duration of gestures.	Touch
AvgGestArea	Mean area occupied by gestures, computed by a minimal adaptive polygon.	Touch
GesturesDecelerationMean	Mean deceleration of gestures.	Touch
GesturesHeightMax	Maximum value of height (y-axis in landscape).	Touch
GesturesHeightMean	Mean value of height (y-axis in landscape).	Touch
GesturesHeightStdDev	Standard deviation of height (x-axis in landscape).	Touch
TouchGestureCount	Number of gestures.	Touch
HeatMapEmptyBlocksCount	Number of screen sectors with no gesture, computed from 10 x10 bins.	Touch
AccelerationMeanMagnitude	Mean accelerometer value irrespective of axis.	Inertia
AttitudeRange_z	Range (max-min) of gyroscope z-axis.	Inertia
AttitudeStdDev_z	Standard deviation of the roll around the z-axis.	Inertia
AttitudeZeroCrossingRate_z	Frequency of sign change of gyroscope x-axis.	Inertia
RotationMin_z	Minimum gyroscope z-axis rotation.	Inertia

Set B. Images for Convolution Neural Networks

Five images were produced for each game for analysis by Convolution Neural Networks (CCN). All touch data over time were parsed into one minute bins and each bin represented as a static image (Figure 6). Only convolutional layers were used with standard dropout [8] values (0.5) and batch normalization [9] in between convolutional layers. Adam [10] optimiser was used with lr=0.001. Batch size was set to 64.



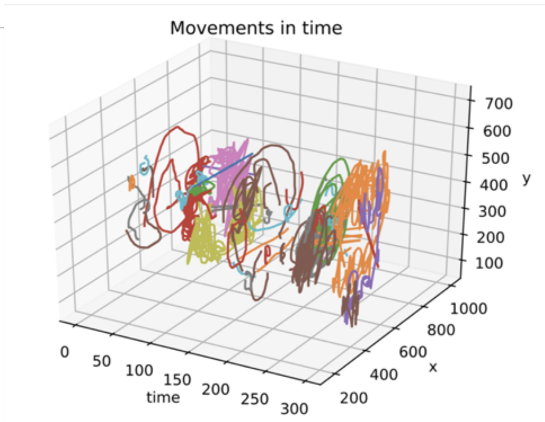
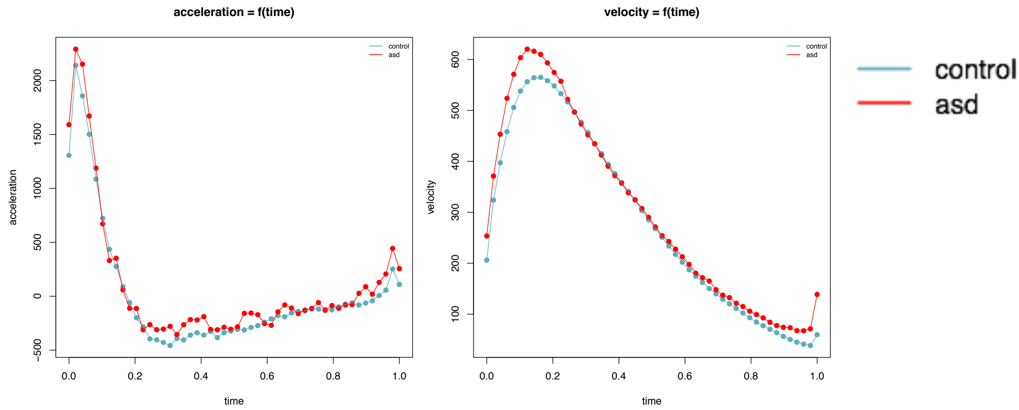


Figure 6. Touch data from two games parsed into five 'image bins' for each game.

Set C. Kinematic Variables for Ensemble Methods

Kinematic features were based only on the touch screen data. Each gesture was time normalised and simple features computed to describe the motor pattern. Data points were binned and features computed for each, *e.g.* mean, median, quartiles and deciles. These data were analysed by (a) session mean and (b) individual movements.



Machine Learning Models

The reduced feature Set A and the kinematic feature Set C were analysed by ensemble methods. Baseline was assessed with usage of logistic regression with regularisation. 10 repetitions of a 10-fold cross-validation procedure was employed on the Training and Validation Participant Set. The algorithm produced then analysed the Test set afresh. Feature Set B was used as an input for Convolutional Neural Networks.

Results

Machine Learning Algorithm Development

1. **Generalised performance is excellent.** New machine learning algorithms trained on the new dataset (n=466) performed well in validation and when tested on the original dataset (n=82).
2. **Reduced features set performance is excellent.** The reduced feature Set A (<17 features) produced comparable result to the original, larger feature set (262).
3. **Kinematic features set performance is excellent.** This suggests purposive motor control alone may be a significant differentiator (biomarker)
4. **Image analysis by CNN is excellent.** This suggests use of space may be a significant differentiator, a metric of attention and interest in engaging an action space

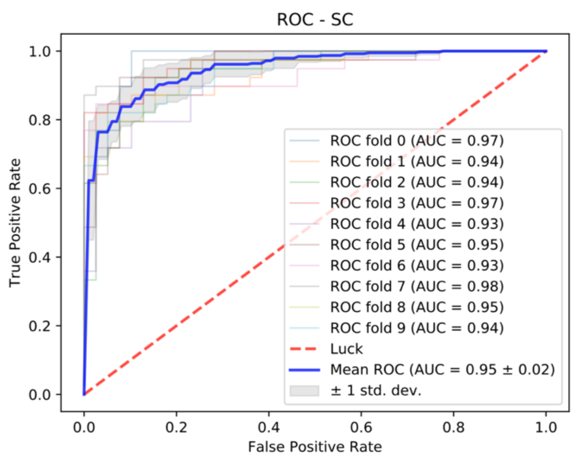
Creativity

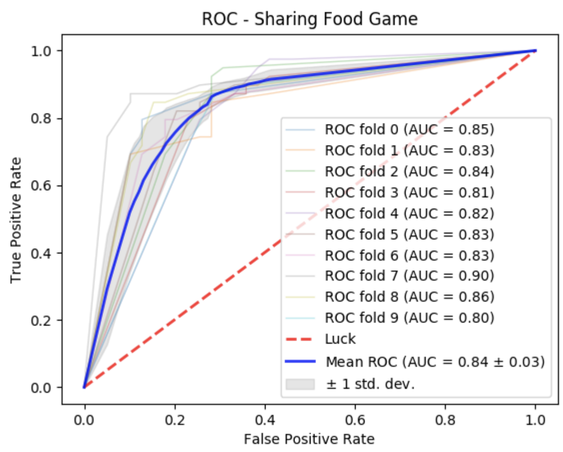
Algorithm	Feature set	Validation sensitivity	Validation specificity	Test sensitivity	Test specificity
Lasso regression	A. Touch & inertia	0.77	0.83	0.77	0.77
Gradient boosting machine	A. Touch & inertia	0.86	0.87	0.85	0.8
SVM	A. Touch & inertia	0.86	0.85	0.75	0.82
Gradient boosting machine	A. Touch, inertia & age	0.87	0.85	0.83	0.82
Convolutional neural network	B. Images	0.92	0.97	0.79	0.89
Convolutional neural network	B. Images + augmentation	0.93	0.97	0.8	0.89
Random forest	C. Kinematic (session mean)	-	-	0.79	0.82

Random forest	C. Kinematic (movements)	-	-	0.85	0.82

Sharing Food

Algorithm	Feature set	Validation sensitivity	Validation specificity	Test sensitivity	Test specificity
Ridge regression	A. Touch & inertia	0.8	0.83	0.36	0.79
Gradient boosting machine	A. Touch & inertia	0.73	0.74	0.56	0.73
SVM	A. Touch & inertia	0.89	0.78	0.49	0.67
Random forest	C. Kinematic (session mean)	-	-	TBD	TBD
Random forest	C. Kinematic (movements)	-	-	TBD	TBD





Conclusions

1. **Machine learning serious game identification of children with autism is valid.** This step in its validation testing is satisfied with larger, more generalised data.
2. **Motor disruption in autism is a significant factor.** Motor kinematic variables alone produced strong differentiation between motor patterns of ASD and TD children, suggesting motor disruption is an important, accessible early biomarker.
3. **Open format gameplay is most effective.** The Creativity game produced the strongest identification with an unstructured, open format colouring game. Maximising affordances for action affords the greatest differences in children's actions.

Impact

Serious game iPad identification of children 3-6 with autism spectrum disorder can be valuable new tool for screening and assessment in the home, clinic, or classroom.

Future Work

This serious tablet game has been commercialised by Harimata Sp.z.o.o and is currently in a phase 3 equivalent diagnostic study of its accuracy (n=760) at the Gillberg Centre for Neuropsychiatry at Gothenburg and the Laboratory for Innovation in Autism in Glasgow (Millar et al., 2018; 2019; ClinicalTrials.gov ID NCT03438994) funded by the EU H2020 SMEI grant number 756079.

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